2641

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PATENT

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IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

In re application of:

Shivnath Babu, et al.

Serial No.: 10/033,199

Filed: December 28, 2001

For: SYSTEM AND METHOD FOR COMPRESSING A DATA TABLE USING MODELS

Group: 2641

Examiner: N/A

Commissioner for Patents
P.O. Box 1450
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Sir:

LETTER TO OFFICIAL DRAFTSMAN

Transmitted herewith are eight sheets of formal drawings to be substituted for the informal drawings initially filed in the above-identified application for patent.

Respectfully submitted,

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Date: MAY 19, 2003

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FIG. 1

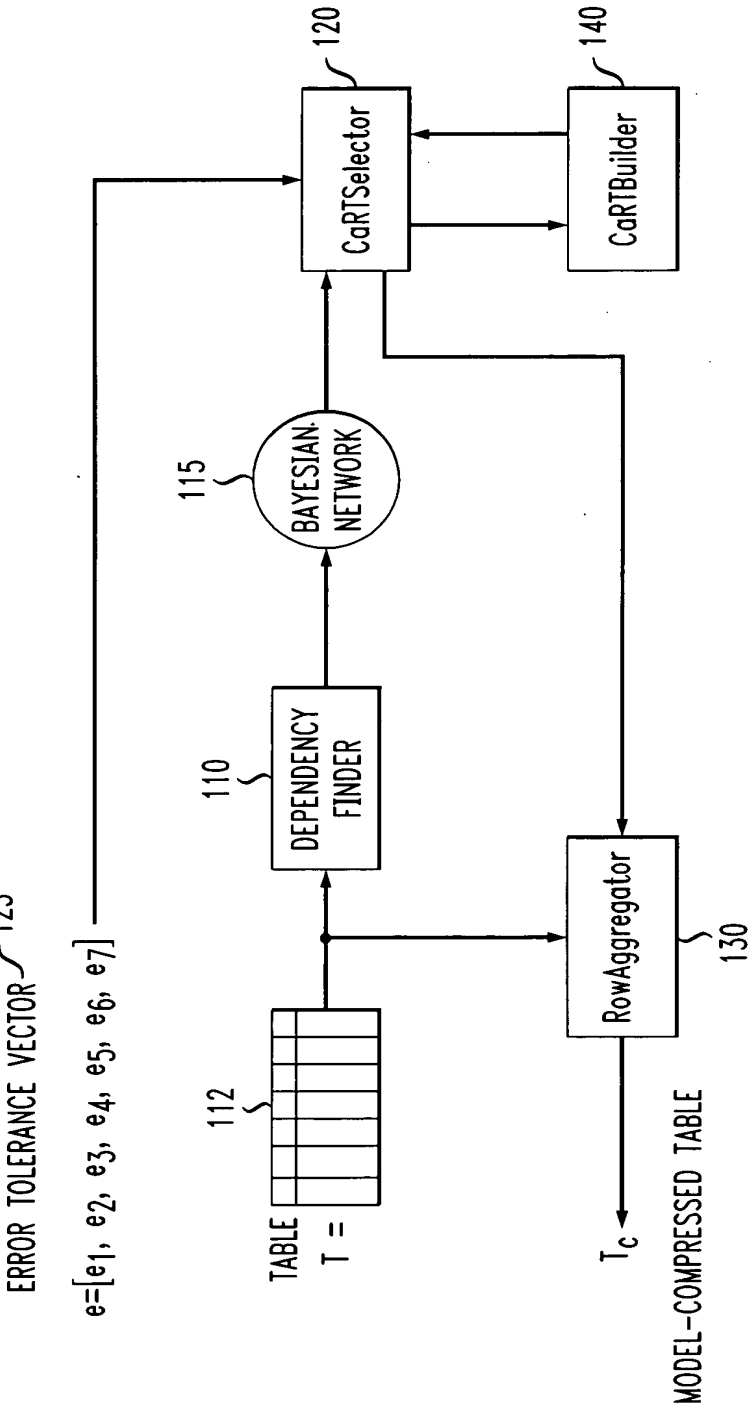


FIG. 2

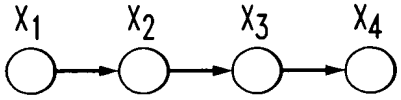
The Greedy CaRT Selection Algorithm

procedure Greedy $(T(X), \bar{e}, G, \theta)$
Input: n-attribute table T and n-vector of error tolerances $\bar{e}$; Bayesian network G on the set of attributes X and threshold θ on the relative benefit for selecting a CaRT predictor.
Output: A set of materialized (predicted) attributes X_{mat} ($X_{pred} = X - X_{mat}$) and a CaRT predictor for each $X_i \in X_{pred}$.

begin
1. $X_{mat} := X_{pred} := \Phi$
2. let $< X_1, X_2, \ldots, X_n >$ be the attributes in X sorted in *topological order* of G
3. for i :=1,...,n
4. if $\Pi(X_i) = \Phi$ then $X_{mat} := X_{mat} \cup \{X_i\}$ /* X_i must be materialized if it has no parents in G */
5. else
6. M := BuildCaRT $(X_{mat} \rightarrow X_i, e_i)$
7. if (MaterCost (X_i) / PredCost $(X_{mat} \rightarrow X_i) > \theta$) then $X_{pred} := X_{pred} \cup \{X_i\}$
8. else $X_{mat} := X_{mat} \cup \{X_i\}$
9. end
10. end

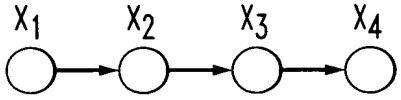
end

FIG. 3A



BAYESIAN NETWORK G

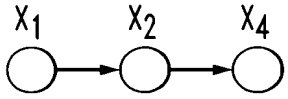
FIG. 3B



-infty 50 110 50

(b) Gtemp (FIRST ITERATION)

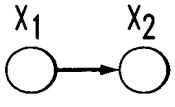
FIG. 3C



-infty -15 45

Gtemp (SECOND ITERATION)

FIG. 3D



-infty -60

Gtemp (THIRD ITERATION)

FIG. 4

The MaxIndependentSet CaRT Selection Algorithm

procedure MaxIndependentSet $(T(X), \bar{e}, G,$ neighborhood() $)$

Input: n-attribute table T and n-vector of error tolerances $\bar{e}$; Bayesian network G on the set of attributes X and function neighborhood () defining the "predictive neighborhood" of a node X_i in G (e.g., $\Pi(X_1)$ or $\beta(X_i)$).

Output: A set of materialized (predicted) attributes X_{mat} ($X_{pred} = X - X_{mat}$) and a CaRT predictor $PRED(X_i) \rightarrow X_i$ for each $X_i \in X_{pred}$.

begin

1. $X_{mat} := X$, $X_{pred} := \Phi$
2. $PRED(X_i) := \Phi$ for all $X_i \in X$, improve := true
3. while (improve $\neq$ false) do
4. for each $X_i \in X_{mat}$
5. mater_neighbors (X_i) := $(X_{mat} \cap \text{neighborhood}(X_i)) \cup \{PRED(X) : X \in \text{neighborhood}(X_i), X \in X_{pred}\} - \{X_i\}$
6. M := BuildCaRT (Mater_neighbors $(X_i) \rightarrow X_i$, e_i)
7. let $PRED(X_i) \subseteq$ mater_neighbors (X_i) be the set of predictor attributes used in M
8. $cost\_change_i := 0$
9. for each $X_j \in X_{pred}$ such that $X_i \in PRED(X_j)$
10. $NEW\_PRED_i(X_j) := PRED(X_j) - \{X_i\} \cup PRED(X_i)$
11. M :=BuildCaRT $(NEW\_PRED_i(X_j) \rightarrow X_j, e_j$
12. set $NEW\_PRED_i(X_j)$ to the (sub) set of predictor attributes used in M
13. $cost\_change_i := cost\_change_i$ + (PredCost (PRED $(X_j) \rightarrow X_j$) - PredCost $(NEW\_PRED_i(X_j) \rightarrow X_j)$)
14. end
15. end

FIG. 4 (cont)

```
16.      build an undirected, node-weighted graph G_temp = (X_mat,
         E_temp) on the current set of materialized
17.      attributes X_mat, where:
18.           (a) E_temp := { (X,Y) : for all pairs X, Y ∈X_pred } ∪
19.                                   { (X_i, Y) : for all Y ∈ X_mat }
20.           (b) weight (X_i) := MaterCost (X_i) -PredCost (PRED(X_i)
              → X_i) +cost_change_i  for each X_i ∈ X_mat
21.      S := FindWMIS (G_temp)     /* select (approximate) maximum
         weight independent set in G_temp
22.                                      as "maximum-benefit" subset of
                                         predicted attributes */
23.      if (Σ_{X∈S} weight (X) ≤ 0) then improve := false
24.      else/* update X_mat, X_pred , and the chosen CaRT predictors */
25.           for each X_j ∈ X_pred
26.                if (PRED (X_j) ∩ S = {X_i}) then PRED (X_j) :=
                     NEW_PRED_i (X_j)
27.           end
28.           X_mat := X_mat - S,  X_pred := X_pred ∪ S
29.      end
30.  end /* while */
end
```

FIG. 5

Algorithm for Estimating Lower Bound on Subtree Cost

```
procedure LowerBound      (N, e_i, b)
Input:  Leaf N for which lower bound on subtree cost is to be
        computed; error tolerance e_i for attribute X_i; bound b
        on the maximum number of internal nodes in subtree
        rooted at N.
Output: Lower bound L(N) on cost of subtree rooted at N.
begin
1.   for i := to r
2.        minOut [i, 0] :=i
3.   for J := 1 to b + 1
4.        minOut [0, j] :=0
5.   1 :=0
6.   for i := 1 to r
7.        while x_i - x_1+1 > 2_ei
8.        1 :=1 = 1
9.    for j := 1 to b + 1
10.       minOut [i,j] := min {minOut[i - 1,j] + 1, minOut [1,j-1]
11.  end
12.  L(N) := ∞
13.  for J := 0 to b
14.       L(N) :=min {L(N) , 2j + 1 + j log (|X_i|) + (j + 1 + minOut
          (r, j+1)) log (|dom(X_i)|)}
15.  L(N) := min {L(N) , 2b + 3 + (b + 1) log (|X_i|) + (b +2) log
     (|dom(X_i) |) }
16.  return L (N)
end
```

FIG. 6

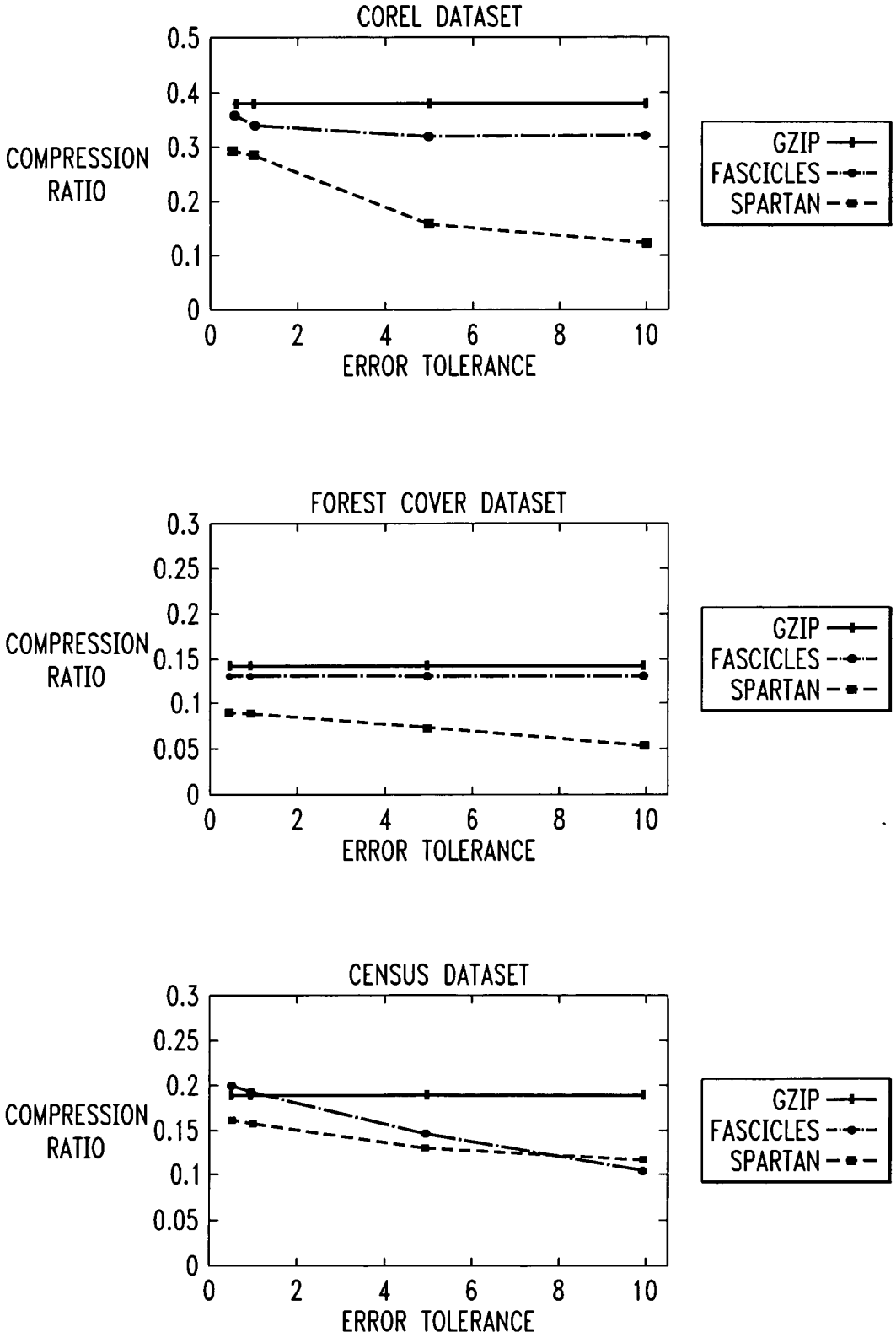


FIG. 7A

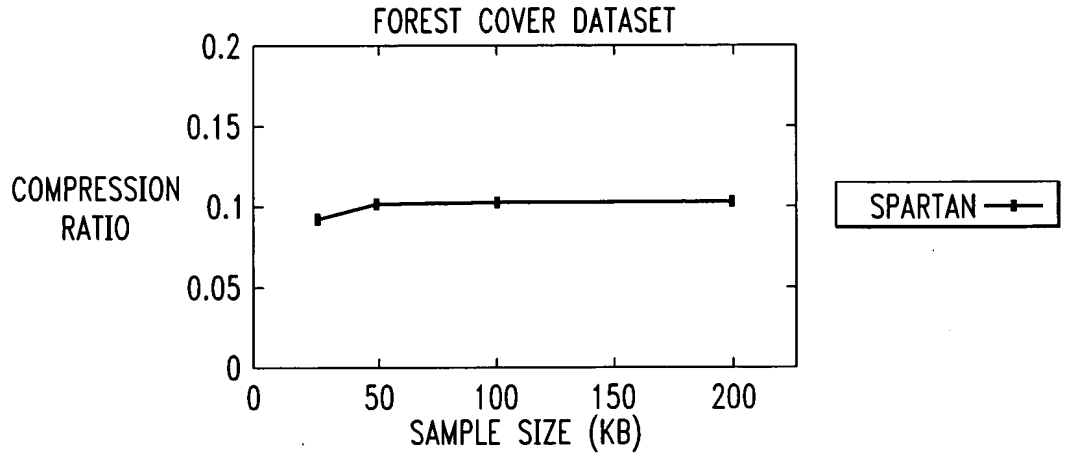


FIG. 7B

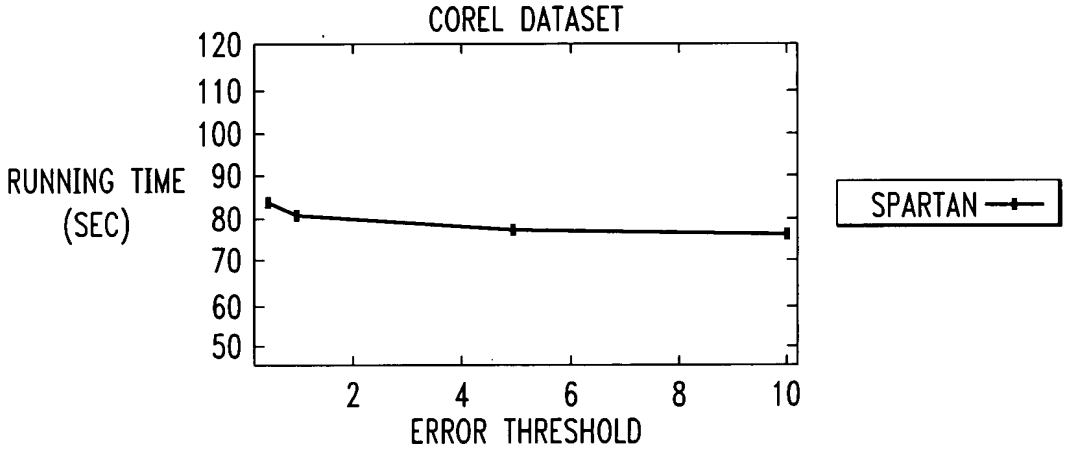


FIG. 7C